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Discriminating contrast discontinuities: asymmetries, dipper functions, and perceptual learning

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Abstract

In a visual search task, a target has to be found among distractors. For two given elements A and B, the search difficulty can depend on which of the two elements is defined as the target, a phenomenon called search asymmetry. Here, we study to what degree an element's ability to 'win' in a search asymmetry depends on its absolute contrast (first-stage signal) and to what degree it depends on its contrast difference from the background (second-stage signal). One quadrant contained a target texture (2×2 Gabor patches of contrast c_{tg}), and the other three quadrants contained distractor textures (2×2 Gabor patches of contrast c_{dt}). These four 'foreground textures' were embedded in a background texture consisting of patches with contrast c_{bg}. The task was to identify which quadrant contained the target. Quadrants are referred to as increments (foreground contrast $c_{fg} > c_{bg}$), or decrements ($c_{fg} < c_{bg}$). We found that the second-stage signal determines which element wins the performance asymmetry, i.e. it is easier to find strong increments (decrements) among weak increments (decrements) than vice versa. A comparison of our data with the prediction of the independent-processing model [Vision Res. 40 (2000) 2677] shows that the observed performance asymmetries are in general too large to be attributed to noise differences alone. Rather, asymmetries might reflect a global competition between salient elements. Moreover, performance asymmetries can reverse during practice. We characterize a dipper-shaped nonlinearity on the second stage: discrimination of increment (decrement) signals x and $x + \Delta x$ first improves for increasing x, and then deteriorates.

Keywords: Contrast discrimination; Texture segmentation; Salience; Visual search; Second stage

1. Introduction

In visual search tasks, observers have to detect a defined target element among distractor elements. Task difficulty can be measured either by reaction times, i.e. how long it takes observers to determine target presence or absence (Treisman & Gelade, 1980; Wolfe, 1994), or by search accuracy, i.e. how often the observer accurately determines target presence or absence in a briefly presented display (Bergen & Julesz, 1983; Sagi & Julesz, 1985; Palmer, Ames, & Lindsey, 1993).

Interestingly, for two given elements A and B, search performance often critically depends on which of the two elements serves as the target, and which takes the role of the distractors. For example, it is easier to find a circle segment among circles than it is to find a circle among circle segments (Treisman & Souther, 1985), and it is easier to find a high-contrast Gabor patch among low contrast patches than vice versa (Sagi, 1990). Similarly, on a black background, it is easier to find a white dot among many gray dots than to find a gray dot among many white dots (Braun, 1994). In many performance asymmetries, one can develop the intuition that it is easier to find the salient element among less salient elements than vice versa. In the context of this study, we will follow this intuition and operationally define salience as an element's ability to win in a performance asymmetry. (Note that we make this terminological choice mainly for convenience. The definition does not affect the conclusions.)

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Two important questions arise. First, there is the question which of any two given elements is more salient. Second, there is the question how salience differences arise during perceptual processing. While the first question can be addressed empirically (Treisman & Souther, 1985; Gurnsey & Browse, 1987; Treisman & Gormican, 1988; Rubenstein & Sagi, 1990; Driver & McLeod, 1992; Cohen, 1993; Meigen, Lagreze, & Bach, 1994; Nagy & Cone, 1996), the second question can be addressed by developing models that account for observed performance asymmetries in the context of general early-vision models.

Models of early vision (Koch & Ullman, 1985; Bergen & Adelson, 1988; Fogel & Sagi, 1989; Sutter, Beck, & Graham, 1989; Malik & Perona, 1990; Rubenstein & Sagi, 1990; Landy & Bergen, 1991; Xing & Gerstein, 1993; Wolfe, 1994; Graham & Sutter, 1998; Itti, Koch, & Niebur, 1998) typically assume two processing stages: the image is first analyzed in different (independent) feature maps, meaning that, for instance, a red foreground region is processed in a different feature map than the green background region in which it might be embedded. In a second processing stage, spatial activity gradients are computed within each feature map. Second-stage border signals from the different maps are then combined into a non feature-specific activation map, on which a decision is based. All these processes are thought to operate in parallel over the visual field.

In the context of these models, performance asymmetries can be attributed to noise differences between the target and the distractor signal (Rubenstein & Sagi, 1990). (The noise of an element refers to the variability of responses on different presentations of that element.) The rationale is that according to signal-detection theory (Green & Swets, 1966), it is easier to find the noisy element in a less noisy background than to find the less noisy element in the noisy background. Rubenstein and Sagi (1990) have shown that differences in the magnitude of response variability can account for performance asymmetries in texture segmentation tasks (Gurnsey & Browse, 1987), such as the asymmetry between textures consisting of randomly oriented Xs and Ls. Specifically, first-stage responses to the randomly oriented Xs are less variable than responses to randomly oriented Ls. This variability is fed into the second stage, where border signals are computed, making the X–X border signals less noisy than the L–L border signals. Consequently, it is easier to detect the X–L border signal in a background of X–X borders, than in a background of L–L borders, accounting for the performance asymmetry.

Here, we investigated how the salience of simple stimuli (Gabor patches) quantitatively depends on their absolute contrast (first-stage signal) and on their spatial contrast difference from the background elements (second-stage signal). We further tested whether we can attribute the observed performance asymmetries to noise differences between target and distractors.

We found that salience of a foreground region depends mainly on the contrast difference to the background elements (i.e. the second-stage signal). Comparison of our data to a simple decision model, referred to as independent-processing model (Zenger & Fahle, 2000), shows that differences in noise between target and distractors cannot account for our data, even if arbitrary local nonlinearities are assumed (such as compressive or expansive nonlinearities, local maximum operators, uncertainty, etc.). Rather, a global competition between salient elements seems to contribute to the performance asymmetries.

We further found that practice could affect the salience of different foreground regions. In some cases, a reversal of asymmetry was observed during practice, meaning that the element that was less salient before practice became the more salient element after practice.

Finally, we observed some interesting nonlinearities in the processing of border signals (second-stage signals): the discrimination of both spatial contrast decrements and spatial contrast increments follows a dipper-shaped function, similar to the dipper functions found for discrimination of absolute contrasts (Legge & Foley, 1980; Wilson, 1980; Bradley & Ohzawa, 1986).

2. Experiment 1: Performance asymmetries

2.1. Methods

2.1.1. Apparatus

Stimulus generation and data collection were controlled by a Silicon-Graphics work station (Indigo 2). Stimuli were presented on a 19 inch Mitsubishi raster monitor with a frame rate of 72 Hz, and a resolution of 1280×1024 pixels. The mean luminance of the screen was $L_m = 45$ cd/m^2, and a gamma correction was applied to ensure linearity of the luminance levels. Stimuli were viewed from a distance of 60 cm, and head position was stabilized by a chin rest and a head bar.

2.1.2. Stimuli

Stimuli were textures consisting of 10×10 vertically oriented Gabor patches. Each Gabor patch is a vertical cosine grating modulated by a Gaussian envelope. The luminance distribution $L(x, y)$ of a single patch is given by

$$L(x,y) = L_m + L_m C \cos((x - x_0)\omega) \times \exp\left(- \frac{(x - x_0)^2 + (y - y_0)^2}{2\sigma^2} \right), \quad (1)$$

with x and y as horizontal and vertical coordinates. The location of the Gabor patch is given by (x_0, y_0), $\omega = 4$ cpd is the spatial frequency of the grating, $\sigma = 0.25$ deg is the standard deviation of the Gaussian envelope, and C is the contrast of the Gabor patch (ranging between 0.0 and 1.0). The patches were arranged on a regular grid, and the distance between neighboring elements was 1 deg.

A typical stimulus is presented in Fig. 1. One quadrant contained a target texture (contrast c_{tg}), the other three quadrants contained distractor textures (contrast c_{dt}). Target and distractor textures always consisted of 2×2 elements and were separated from the texture edges by one row and one column. Target and distractor textures are also referred to as foreground. The remaining elements are called background elements. When the foreground contrast (c_{fg}) exactly equals the background contrast (c_{bg}), quadrants are referred to as 'homogeneous quadrants'. When there is a spatial contrast difference, quadrants are called either increments (when $c_{fg} > c_{bg}$) or decrements (when $c_{fg} < c_{bg}$).

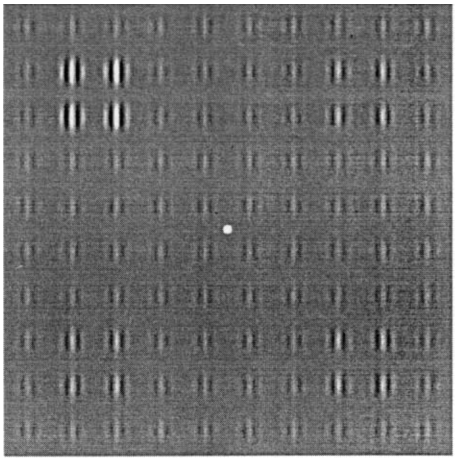

Fig. 1. A typical stimulus for $c_{tg} > c_{dt} > c_{bg}$. The upper left quadrant contains the target; the other three quadrants contain distractors. Target and distractor textures consist of 2×2 elements and are separated from the texture edges by one row and one column. A fixation point is presented in the stimulus center.

Table 1
Contrast parameters used in different conditions. In the H-target condition observers searched for the high-contrast target, while they searched for the low-contrast target in the L-target condition

Condition		c_{tg}	c_{dt}	c_{bg}
Low-contrast condition	H-target	0.20	0.10	0.0–1.0
	L-target	0.10	0.20	0.0–1.0
Med-contrast condition	H-target	0.50	0.40	0.0–1.0
	L-target	0.40	0.50	0.0–1.0
High-contrast condition	H-target	0.70	0.60	0.0–1.0
	L-target	0.60	0.70	0.0–1.0

In each condition, the background contrast was varied in different blocks over the entire contrast range. Observer SP used a foreground contrast of 0.16 instead of 0.20 in the low-contrast condition.

2.1.3. Procedure

A fixation point in the center of the screen was visible throughout the experiment. Observers initiated each trial by pressing the space bar. After a 500 ms blank stimulus (homogeneously gray screen with fixation point the stimulus was presented for 83 ms and then replaced by a blank screen. The observer's task was to identify which of the four quadrants contained the target, and the decision was indicated by specified keys, arranged on the keyboard corresponding to the quadrants on the screen. Within a single block of 50 trials, none of the parameters varied, and accuracy (i.e. the percentage of correct target localizations) was measured as a function of target contrast, distractor contrast, and background contrast. Observers were always aware of the parameter setting within a block.

The experiment consisted of three main conditions that differed in the magnitude of foreground contrasts. In the low-contrast condition, observers had to discriminate between foreground regions of contrasts 0.10 and 0.20. These contrast levels were set to 0.40 and 0.50 in the med-contrast condition, and to 0.60 and 0.70 in the high-contrast condition. (Observer SP used slightly different parameters in the low-contrast condition: the foreground contrasts were 0.10 and 0.16 instead of 0.10 and 0.20.) Each session was restricted to one of the three main conditions, and observers performed six sessions in each condition. Sessions were run in a defined order, e.g. low—high—med—low—high—med— etc., with different ordering for different observers.

Each main condition contained two subconditions: in the H-target condition, the target contrast was higher than the distractor contrast, whereas in the L-target condition, the target contrast was lower than the distractor contrast. To avoid confusing observers, each subcondition was tested separately, i.e. observers started either with the H-target or the L-target condition, with alternating order in different sessions. Between the different blocks, the background contrast was varied pseudo-randomly in the entire contrast range (between 0.0 and 1.0). The different conditions are summarized in Table 1.

The paradigm described here differs somewhat from classical texture-segmentation or visual-search tasks. It can be considered as a meta-search task, because observers not only have to segment foreground textures from the background texture, but also have to perform a search task (they have to choose the target among distractors). Due to this design, the use of the term 'performance asymmetry' can be confusing. In the context of the present study, two tasks are considered asymmetric when target and distractors are exchanged,

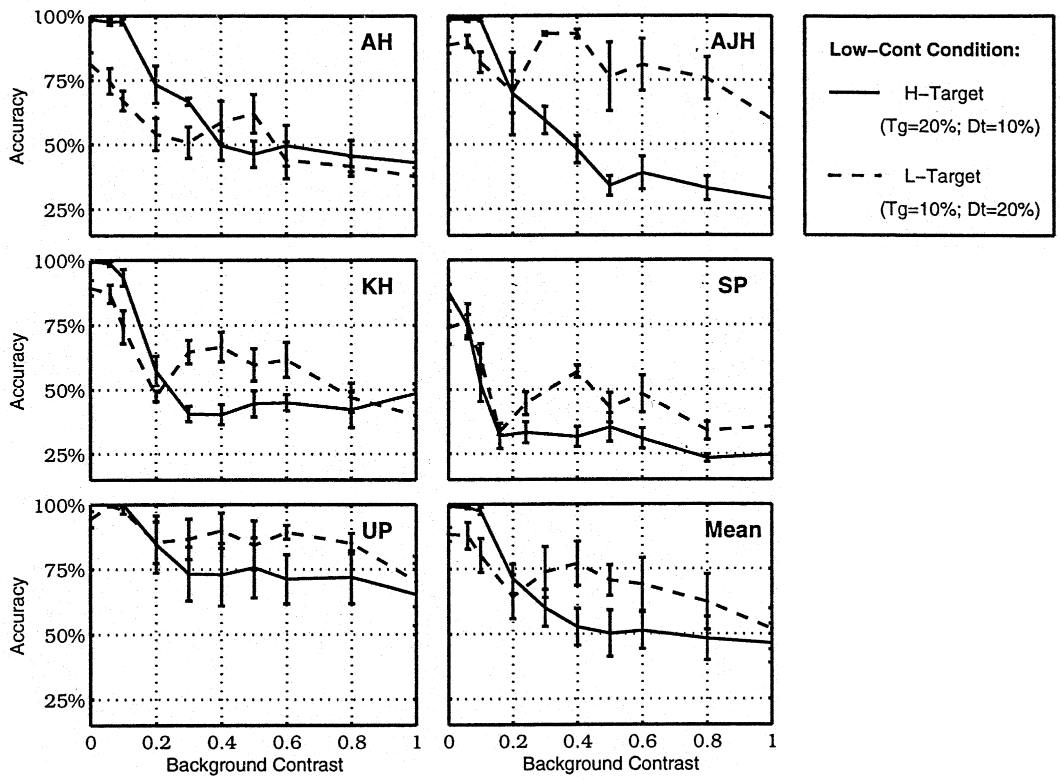

Fig. 2. Results of the low-contrast condition, showing performance in H-target and L-target conditions is plotted as a function of background contrast for the five observers. Error bars represent standard erors of the mean across different sessions or observers. Note that Observer SP was using slightly different parameters (foreground contrasts of 0.16 instead of 0.20) and is thus not included in the mean. For background contrasts of 30% and below, it is (on average) easier to find the high-contrast target, and for background contrasts above 30%, it is often easier to find the low-contrast target.

and not when foreground and background are exchanged.

2.1.4. Observers

Five naïve observers with normal or corrected-to-normal vision participated in the experiment. The experiment consisted of 18 sessions, each lasting for approximately 1 h. Some observers performed more than one session per day. In this case, the sessions were separated by at least 2 h.

2.2. Results

Results of the low-, med-, and high-contrast condition are shown in Figs. 2–4, respectively.

2.2.1. Performance asymmetries

In spite of variability across observers in the magnitude of the performance asymmetries (compare, for example, observers AH and SP; Figs. 3 and 4), the following general pattern can be observed. For a low background contrast, performance is better in the H-target condition, while for a high background contrast, performance is better in the L-target condition. It is thus usually easier to find the strong increment among the weak increments than to find a weak increment among strong increments, and it is furthermore easier to find the strong decrement among the weak decrements, than to find a weak decrement among strong decrements. In other words, the stronger the second-stage signal, the more salient is the element.

A curious finding is that the sign of the performance asymmetry did (on average) not reverse at a background contrast between target and distractor contrast, but reversed at a higher background contrast. In other words, when observers had to find the decrement among three homogeneous quadrants ($c_{tg} < c_{dt} = c_{bg}$; ‘1-decrement task’) they were worse than when they had to find the homogeneous quadrant among three decrements ($c_{dt} < c_{tg} = c_{bg}$; ‘3-decrement task’). A more detailed analysis revealed that this effect developed during practice. Fig. 5 shows the performance difference between 1-decrement and 3-decrement tasks (pooled across low-, med-, and high-contrast conditions) as a function of practice time. In the first session, the difference is positive, meaning that performance was better in the 1-decrement task (although this difference was not significant). Later, the asymmetry reversed, and the 3-decrement task became easier. Note that the decrease in Fig. 5 does not reflect a simple performance improvement, like in classical learning curves, but it reflects the improvement in one condition relative to another condition. This learning effect was addressed in more detail in Experiment 2.

2.2.2. Dipper functions

Within the different contrast conditions (low-, med-, and high-contrast conditions) the foreground contrasts remained the same, i.e. the first-stage signal was not varied. Variations in the background contrast affect, however, the second-stage signal. A quick glance at the results demonstrates that this second-stage signal has nonlinear effects on performance.

A clear example of such effects is seen in the H-target condition of the high-contrast condition (Fig. 4, mean values): when observers have to find an increment among three homogeneous quadrants ($c_{tg} = 0.70$, $c_{dt} = c_{bg} = 0.60$), observers are able to choose the correct quadrant in 61.3% of the trials. A decrease in the background contrast leads to an increase in accuracy. The highest accuracy level (79.5%) is reached for a background contrast of 0.40. For a further decrease in background contrast, performance deteriorates again such that the accuracy is only 62.2% for a background contrast of 0.00. A similar effect is seen in the med-contrast condition (Fig. 3, mean values): in the H-target condition, decreasing the background contrast from 0.40 to 0.30 leads to a performance improvement, while performance deteriorates for a further decrease in background contrast. In the low-contrast condition (Fig. 2), the effect is difficult to assess because of ceiling effects.

This behavior recalls the dipper functions obtained in typical discrimination tasks: if two stimuli x and $x + \Delta x$ have to be discriminated, discrimination thresholds first decrease and then increase for increasing pedestal, x (Nachmias & Sansbury, 1974; Legge & Foley, 1980; Wilson, 1980; Bradley & Ohzawa, 1986). The only difference here is that the critical signal (x) is a second-stage signal (resulting from a spatial contrast difference) rather than a first-stage signal (which depends on contrast).

A dipper effect is observed also for the discrimination of decrements. In the L-target condition of the low-contrast condition (Fig. 2), the average performance in the 1-decrement task is 58.2% ($c_{tg} = 0.10$; $c_{dt} = c_{bg} = 0.20$, or 0.16 for observer SP). An increase in background contrast from 0.20 to 0.40 leads to an increase in performance up to 73.1%. When the background contrast is further increased (decrements become stronger), performance decreases again. A weak dipper effect might also exist in the med-contrast condition (Fig. 3, L-target condition).

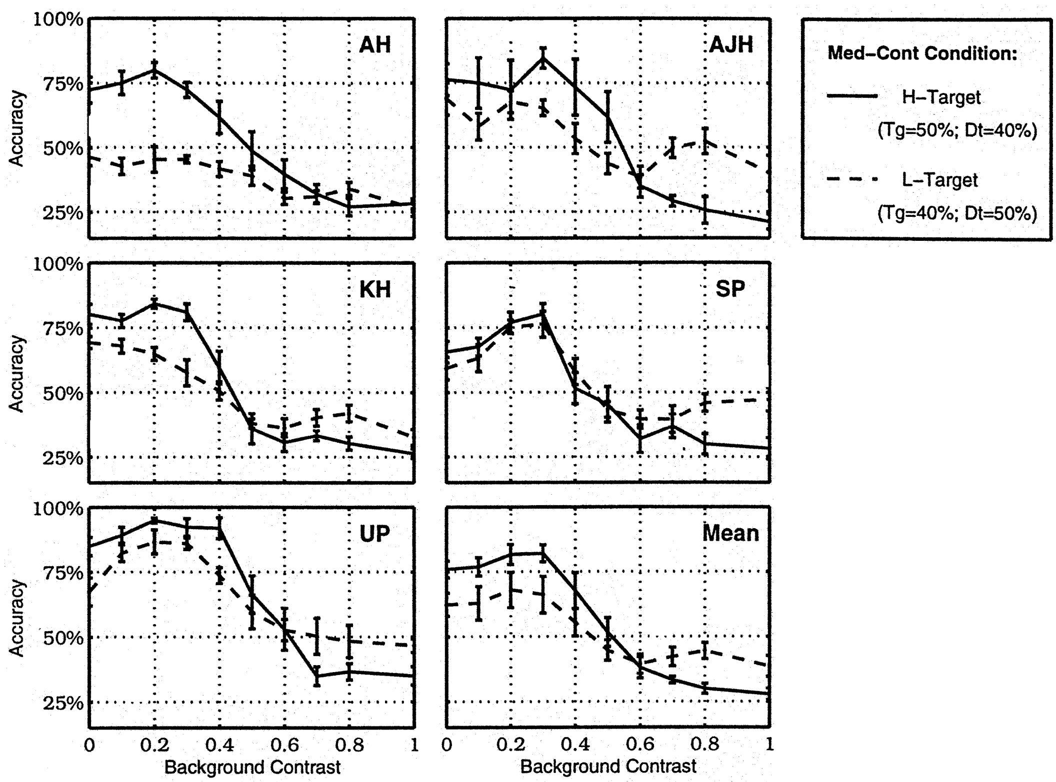

Fig. 3. Results of the med-contrast condition. Error bars represent standard errors of the mean across different sessions or observers. Performance asymmetries between the H-target and L-target conditions typically reverse at a background contrast around 0.5.

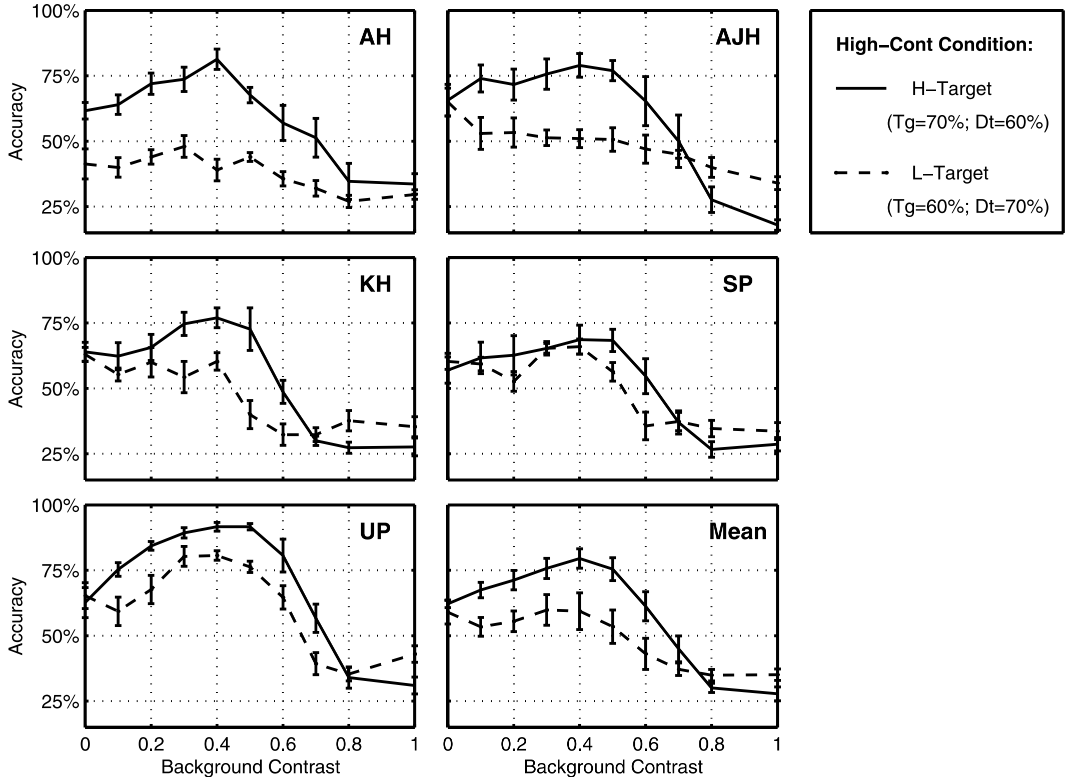

Fig. 4. Results of the high-contrast condition. Error bars represent standard errors of the mean across different sessions or observers. For low background contrasts, it is easier to find the high-contrast target, whereas for high background contrasts it is easier to find the low-contrast target. Asymmetries reverse typically at a background contrast of about 0.7.

In general, it seems that, for the discrimination of decrements, the dipper is more prominent in the L-target condition, whereas for the discrimination of increments, it is more prominent in the H-target condition.

3. Experiment 2: Practice effects

We conducted a series of experiments to further investigate the practice effects observed in Experiment 1. The general methods were very similar to those of Experiment 1.

3.1. Experiment 2a: Stability of effect—perceptual correlate

Experiment 1 contained relatively few measurements in the critical conditions. To make sure that the better performance in the 3-decrement vs. 1-decrement task was a real effect, and not due to, for example, suboptimal decision criterions, observer BZ (the first author, a very well-practised observer in these tasks) performed several sessions in a row in each of the two conditions, to give plenty of time for an adjustment of decision strategies.

3.1.1. Methods

Five sessions in the 3-decrement task ($c_{tg} = c_{bg} = 0.5$; $c_{dt} = 0.4$) were followed by 5 sessions in the 1-decrement task ($c_{tg} = 0.4$; $c_{dt} = c_{bg} = 0.5$). Each session consisted of 20 blocks of 50 trials each.

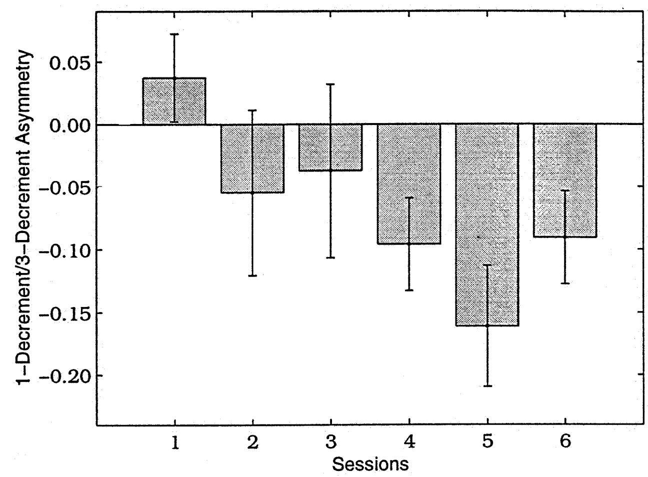

Fig. 5. Performance asymmetry (difference in per cent correct values) between 1-decrement and 3-decrement tasks as a function of practice time (data are pooled across all observers and conditions). In the first session, performance in the 1-decrement task is better; later, the asymmetry reverses. Error bars represent the standard error of the mean across observers.

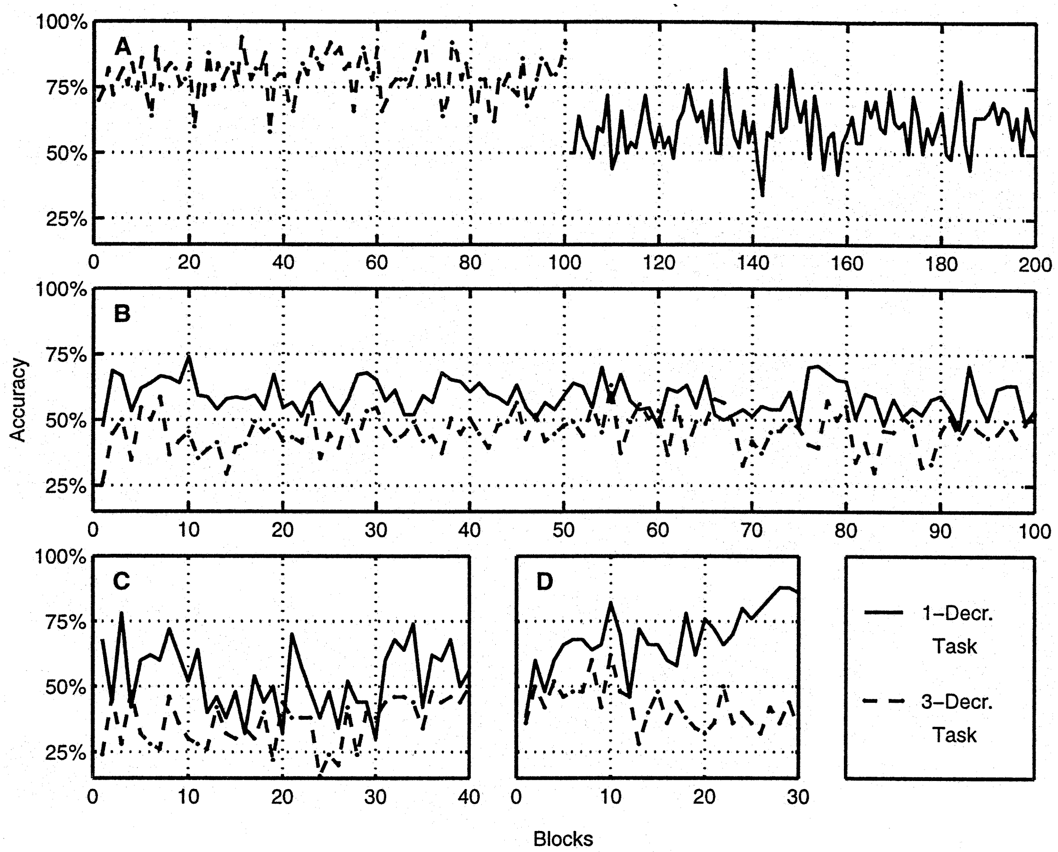

Fig. 6. Performance in 1-decrement and 3-decrement tasks as a function of practice time. In Experiment 2a, performance was stable in both the 3-decrement and 1-decrement, with the 3-decrement performance consistently better than the 1-decrement performance (A; observer BZ); the surprising finding that the homogeneous quadrant is more salient than the decrements can be better understood considering the perceptual impression (Fig. 7) reported by this observer (the first author). In Experiment 2b, practice of 1-decrement and 3-decrement tasks in alternating blocks for 10 sessions did not lead to a performance improvement either (B; average over all three observers). In experiment 2c, no consistent learning effect was observed for observer FB (C), but a significant increase in performance asymmetry was found for observer MP (D). Observer MP also reported an interesting perceptual impression (see Fig. 7), which is opposite to that reported by BZ.

3.1.2. Results

Results are shown in Fig. 6A. The performance in the 3-decrement task is clearly better than performance in the 1-decrement task. This effect seems very stable.

An surprising perceptual observation was that the homogenous quadrants were perceived as if they were increments, i.e. the foreground region appeared to pop out due to a higher apparent contrast, even though there was no physical contrast difference between foreground and background. Thus, the 3-decrement task was perceptually more like the (easy) 1-increment task, while the 1-decrement task was perceptually more like the 3-increment task (see Fig. 7). Upon inquiry, this perception was confirmed by several observers of Experiment 1.

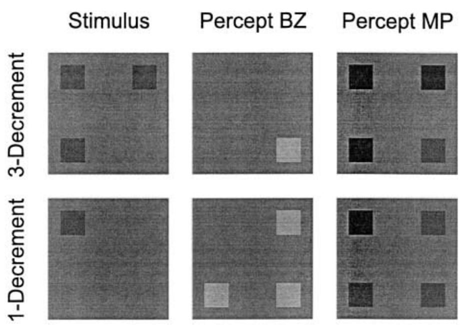

Fig. 7. In these schematic stimulus representations, bright areas represent areas with high-contrast Gabor patches, while darker areas represent areas with lower-contrast Gabor patches. For observer BZ, the foreground regions appear of a higher contrast than they are, thus the 3-decrement and 1-decrement stimuli look like 1-increment and 3-increment stimuli, respectively. For observer MP, foreground regions appear of a weaker contrast, and he sees in both the 3-decrement and the 1-decrement task always four decrements (of different strength).

3.2. Experiment 2b: Practice of 1-decrement and 3-decrement tasks only

3.2.1. Methods

Three naïve observers were asked to perform 10 sessions of alternating blocks in the 1-decrement and

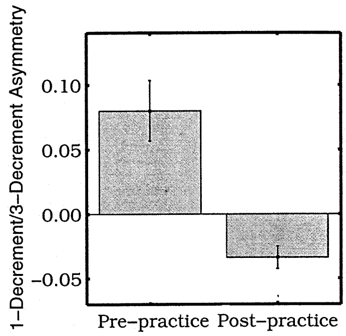

Fig. 8. Data of Experiment 2d, averaged across all three observers. The performance difference between 1-decrement and 3-decrement performance reversed its sign after practice. Error bars indicate the standard error across observers. The decrease in performance asymmetry was highly significant.

3-decrement tasks. Again, each session consisted of 20 blocks with 50 trials each. Adequate contrast levels were determined in an initial pre-practice session ($c_{bg} = 0.60$; $c_{tg} = 0.35$ or 0.60; $c_{dt} = 0.60$ or 0.35).

3.2.2. Results

The average over all observers is shown in Fig. 6B. Unexpectedly, practice had almost no effect on performance and certainly did not lead to a reversal of the 3-decrement and 1-decrement performance asymmetry.

3.3. Experiment 2c: Additional practice of conditions with high background contrast

The absence of practice effects in Experiment 2b suggests that mixing of different contrast conditions (like in Experiment 1) may have been critical in obtaining a practice effect. In the next experiment, practice sesssions with a high background contrast were included.

3.3.1. Methods

This experiment was very similar in that the first and last practice session consisted only of alternating 1-decrement and 3-decrement tasks. Contrast levels were again determined in an initial pre-training session (FB: $c_{bg} = 0.60$; $c_{tg} = 0.60$ or 0.30; $c_{dt} = 0.30$ or 0.60; MP: same, but 0.35 instead of 0.30). In the intermediate 2–4 sessions, the two observers performed also conditions with the same foreground contrasts, but high background contrast ($c_{bg} = 1.0$).

3.3.2. Results

While observer FB showed no consistent practice effect (Fig. 6C), there was consistent increase in performance asymmetry for observer MP (Fig. 6D). The change in performance asymmetry is highly significant (correlation between performance difference and time; $P < 0.001$). Moreover, this observer shared with the experimenter, without being in any way asked about it, that he had the ‘weired’ impression that the four foreground textures now appeared to be of a lower contrast than the surrounding background (see Fig. 7). Note that this is the opposite of the effect described by BZ, who perceived an increase in foreground contrast.

3.4. Experiment 2d: Practice biased for H-target condition

Next, we tested whether the performance asymmetry between 1-decrement and 3-decrement tasks can be biased in favor of the 3-decrement performance if practice is biased towards search for the high-contrast target.

3.4.1. Methods

During four practice sessions, observers always searched for a high-contrast element ($c_{tg} = 0.6$) among low-contrast elements ($c_{dt} = 0.4$). In different blocks, the background contrast, c_{bg}, was pseudo-randomly varied between 0.40, 0.48, 0.54, and 0.60. Before and after practice, observers performed two sessions of a pseudo-random mixture of the 3-decrement, 1-decrement, 3-increment and 1-increment tasks (c_{bg}, c_{tg}, and c_{dt} were either 0.40 or 0.60, depending on the task).

3.4.2. Results

In the pre-practice data, all observers performed better in the 1-decrement than in the 3-decrement task. After practice, this asymmetry reversed in all three observers. The mean performance asymmetries between 1-decrement and 3-decrement tasks averaged across all three observers are shown in Fig. 8, separately for the before practice and after practice conditions. The decrease in performance asymmetry was highly significant ($P < 0.01$).

3.5. Summary

We found that the performance asymmetry between the 1-decrement and 3-decrement tasks can either increase or decrease (or stay constant) as a result of practice. The behavioral effect (change in performance asymmetry) is accompanied by a perceptual change, in which the foreground contrast appears either stronger or weaker than background elements of equal physical contrast. Our preliminary results suggest that practice set (in addition to inter-observer differences) may affect the ‘direction of learning’.

4. Modeling

One goal of our study was to understand how salience is computed by the brain; in particular, we wanted to know whether noise differences between target and distractor can account for the observed asymmetries. To this end, we compared our data with the independent-processing model prediction that we have recently derived (Zenger & Fahle, 2000).

4.1. Independent-processing model (IPM)

Performance in a 2AFC task corresponds to the area under the receiver operator characteristic, or ROC curve (Green & Swets, 1966). Performance in a 4AFC task is obtained by first taking the ROC curve (which we call here $f(x)$, Fig. 9) to the power of three, and then integrating the resulting curve (Green & Swets, 1966). Performance in the asymmetric task is obtained by mirror-reversing the ROC $f(x)$ on the diagonal line $y = 1 - x$ (this corresponds to the exchange of target and distractor), taking the resulting function (which we call $g(x)$, Fig. 9) to the power of 3 and then integrating (see Fig. 9). We have recently shown that, independent of the shape of the underlying distributions, performance asymmetries cannot become arbitrarily large, but that for any given performance level in the easy task (P_{easy}), there is a lower bound for performance in the difficult task ($P_{\mathrm{difficult}}$), which is given by (Zenger & Fahle, 2000):

$$P_{\mathrm{difficult}} = \frac{1}{27}(16P_{\mathrm{easy}}^3 + 6P_{\mathrm{easy}} + 5). \quad (2)$$

The assumptions that form the basis of this model are (1) an ideal-observer decision and (2) independent processing of the different elements, i.e. the response distribution for elements A and B are fixed, and do not change depending on what other elements are present in the display. We therefore refer to this model as the independent-processing model (IPM).

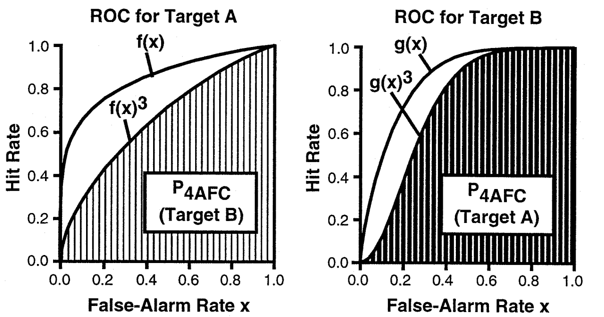

Fig. 9. ROC curves (hit rate vs. false-alarm rate) for two elements A and B. The left-hand panel shows the ROC curve when A is the target, and the right-hand panel shows the ROC when B is the target. The two curves (f and g) are mirror symmetric with respect to the negative diagonal ($y = 1 - x$). Performance in the 4AFC with A as the target is obtained by taking the ROC for target B to the power of 3 and then integrating, while performance in the asymmetric task is obtained by taking the ROC for target A to the power of 3 and then integrating. These two performance levels are not completely independent, and an upper bound for maximal performance asymmetries can be derived independent of the underlying distributions of A and B. (Figure taken from Zenger & Fahle, 2000.)

Here, we wanted to test whether our data are consistent with this limit imposed by the IPM. Note that the model has to be considered violated as soon as there exists a condition in which asymmetries are significantly above the model limit, even if, in other conditions, the asymmetries lie within the limits. Thus, simply showing that asymmetries 'on average' lie within the bounds is not sufficient, since small asymmetries in some conditions might potentially mask above-limit asymmetries in other conditions. However, if all conditions are considered individually, some asymmetries will exceed the model limit for purely statistical reasons. As a trade-off, we averaged over all conditions in which asymmetries were observed rather consistently.

Specifically, the following data were considered: Experiment 1: We used data from all those conditions that showed an asymmetric trend across observers ($p < 0.10$; low-cont condition: $c_{\mathrm{bg}} = 0.0$, 0.4, 0.5, 0.6; med-cont condition: $c_{\mathrm{bg}} = 0.0$, 0.1, 0.2, 0.3, 0.4, 0.7, 0.8, 1.0; high-cont condition: $c_{\mathrm{bg}} = 0.1$, 0.2, 0.3, 0.4, 0.5, 0.6, 1.0). Experiment 2abc: All the 1-decrement and 3-decrement data were used. Experiment 2d: In this experiment, the 1-decrement and 3-decrement asymmetry reversed during the experiment, and the asymmetry was thus on average small. Therefore, we used only the data from the 1-increment and 3-increment tasks.

Results of individual blocks for the 'difficult task' and the 'easy task' were paired. Then, each measurement in the easy task was used to compute the lower bound for the difficult task, using Eq. (2), from which the actual performance was subtracted. Positive values imply that the actual performance was below the lower bound of the model, thus indicating a model failure. The average model deviations for each observer are shown in Fig. 10. We found that for 11 out of 14 observers, performance asymmetries exceeded the model limit significantly ($P < 0.05$; Fig. 10), and we thus conclude that the IPM is violated under the conditions of the experiments reported here.

5. Discussion

Observers had to localize a target texture among three distractor textures that were all embedded in a background texture. The percentage of correct target localizations was measured as a function of target contrast, distractor contrast, and background contrast. The contrast parameters were varied systematically in different conditions.

5.1. Performance asymmetries

The general pattern of results can be summarized as follows: when discriminating increments, it is easier to

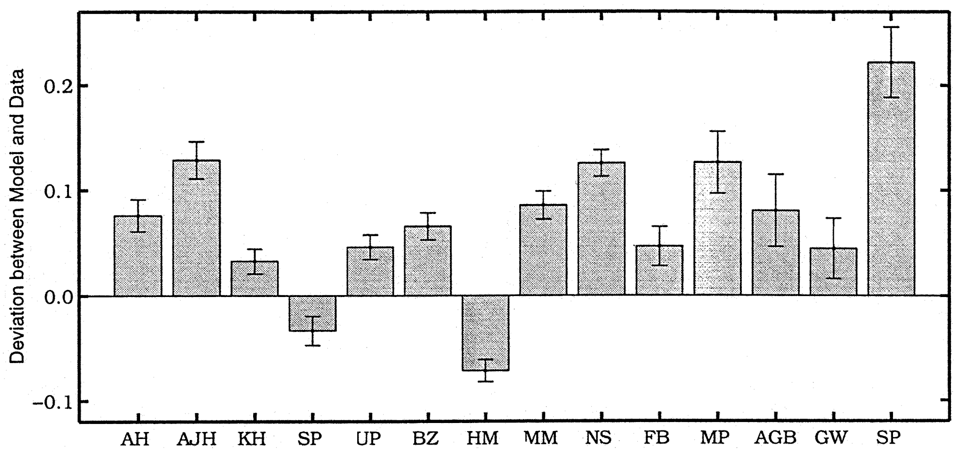

Fig. 10. Difference between lower bound for the difficult task given by the IPM and actual performance in the difficult task. Positive values indicate a model failure (the lower bound is higher than the actual data). Eleven out of the 14 observers participating in Experiment 1 and 2 (1: AH, AJH, KH, SP, UP, 2a: BZ; 2b: HM, MM, NS; 2c: FB, MP; 2d: AGB, GW, SP) showed asymmetries that were consistently larger than predicted by the IPM; the IPM is thus rejected.

find the strong increment among weak increments than vice versa, and when discriminating among decrements, it is easier to find the strong decrement among weak decrements than vice versa. Consequently, it is not true that it is always easier to find the high-contrast target among the low-contrast distractors (H-target condition) than to find a low-contrast target among high-contrast targets (L-target condition). This shows that the salience of a foreground region does not so much depend on the absolute contrast level of the foreground region (first-stage signal), but rather depends on its spatial contrast difference to the background (second-stage signal). Interestingly, the background contrast at which the H-target and L-target conditions were equally difficult was slightly higher than both the target and the distractor contrasts (and not as one would expect, between the two); this shift developed only after practice and was usually not observed in the naïve observers.

Current models of spatial-discontinuity detection assume that detection depends on local filtering of the image, and local nonlinearities (see Section 1). In the context of such models, performance asymmetries can be attributed to noise differences between target and distractor; namely, it is easier to find a noisy signal in a quiet background than to find a quiet signal in a noisy background (Rubenstein & Sagi, 1990). Recently, we have shown that one can derive an upper bound on performance asymmetries, based on two assumptions: independent processing of target and distractors, and an ideal-observer decision (Zenger & Fahle, 2000). We call the model that is consistent with these assumptions the independent-processing model (IPM). In the context of our experiments, both assumptions might appear plausible. First, the ideal-observer assumption is common to most models, and does not appear problematic here (as discussed in detail elsewhere (Zenger & Fahle, 2000)). Second, independent processing of target and distractors seems plausible given the large distance between them (5 deg and more, corresponding to 20 cycles of the Gabor period). At these large distances, interactions are not expected (Cannon & Fullenkamp, 1991; Polat & Sagi, 1993). Nevertheless, a comparison of our data and the predicted upper bound of the IPM shows that the data are not consistent with the prediction, and thus the model has to be rejected. In other words, if the observed asymmetries could be accounted for by differences in noise, they would have to be smaller than they actually are. The large magnitude of the asymmetries thus demonstrates that salience differences between target and distractor cannot be attributed solely to noise differences.

The most likely reason for the failure of the IPM model is a violation of the independent-processing assumption (Zenger & Fahle, 2000). For example, there might be competitive interactions between salient elements (mutual inhibition, global response normalization, etc.). In the context of such a global-competition model, an element's salience might not be mediated by its noise level at the decision stage, but instead by its response level. If many salient elements are presented, they will reduce each other's response by competitive interactions. However, if only one salient element is presented, no such response reduction occurs. Thus, the response difference between target and distractor will be different in the two tasks, explaining why a performance asymmetry occurs.

The global competition or global-normalization model is reminiscent of the original explanation for performance asymmetries by Treisman and colleagues (Treisman & Souther, 1985; Treisman & Gormican, 1988). They assume that the decision is based on the pooled response across the whole feature map. Assume that the salient elements produce a response, r, and the non-salient elements produce no response. In one task, observers need to distinguish between responses of 0 and r, and in the other task they need to distinguish between responses of $3r$ and $4r$. Following Weber's Law, the latter task is more difficult, thus explaining the performance asymmetry. Note, however, that the model assumes that responses are pooled across first-stage feature maps (such as the maps for red or horizontal), while one would have to assume that responses are pooled across second-stage feature maps (containing border signals) to account for the present data.

5.2. Perceptual learning

We found that the magnitude and sign of a given performance asymmetry can change during practice. In particular, we found that naïve observers are usually better in the 1-decrement task than in the 3-decrement task (Experiment 1, Experiment 2bcd), while practised observers are often better in the 3-decrement task (Experiment 1, Experiment 2ad). The reversal of asymmetry was reflected in a perceptual change, which led to an overall increase in the perceived foreground contrast, and made decrements look like homogeneous quadrants, and homogeneous quadrants look like increments. One observer described a perceptual change in the opposite direction: for him, the foreground regions appeared now of a weaker contrast, and homogeneous quadrants looked to him like decrements. Interestingly, he also showed a learning effect in the opposite direction: instead of a reversal, he revealed an increase in the asymmetry between 1-decrement and 3-decrement task. Note that the perceptual change seems to justify our operational definition of salience, because after practice, the homeogenous quadrant (which looked like a increment) appeared more salient than the decrement (which looked like a homogneous quadrant). Our operational definition is consistent with that change.

Perceptual learning effects in texture segmentation tasks and popout experiments are very common (Karni & Sagi, 1991; Ahissar & Hochstein, 1993). In most of these studies, observers have to detect a region with elements oriented differently than the background. In other words, target and distractors are processed in different 'feature maps'. In our experiments, all elements had the same orientation, and all conditions presumably excited the very same feature maps. We believe that this design may make it easier to constrain models of learning, since cross-orientation interactions do not have to be considered, reducing the number of free parameters. In other words, target and distractors are processed by the same unit, so each change that affects the target will automatically affect the distractors.

What is the mechanism of learning? The relative increase in apparent foreground contrast with respect to the apparent background contrast (Fig. 7) suggests a decrease in lateral inhibition from the background to the foreground. This hypothesis is appealing because it is a natural extension of mechanisms suggested for perceptual learning in contrast masking: in those studies, learning was found to reduce inhibition from the mask to the target (Zenger & Sagi, 1996; Dorais & Sagi, 1997). To explain the learning effect in the opposite direction (Experiment 2c), there are two obvious possibilities: first, lateral inhibition from the background to the foreground might increase (instead of decrease). Alternatively, the inhibitory interactions from foreground to background (instead of those from background to foreground) might decrease. Following the above analogy to contrast masking studies, the latter scenario would suggest that observers do not treat the low-contrast foreground as the target, but instead the high-contrast patches surrounding the target.

Indeed, in the context of a model with lateral suppressive interactions, such a switch in strategy would seem plausible: assume that each first-stage unit receives some divisive input from the neighboring units. Such local gain-control mechanisms have been inferred from psychophysical and physiological data and are found to be particularly strong in the periphery (Snowden & Hammet, 1998; Xing & Heeger, 2000; Zenger, Braun, & Koch, 2000; Zenger & Koch, 2001). Since salience is likely to be mediated by the magnitude of response that each element achieves (see above), it seems straightforward to assume that discrimination performance mostly relies on these large signals. In the increment discrimination task, the strongest signals will correspond to the foreground region, while in the decrement discrimination task, the strongest signals will be evoked by the high-contrast patches bordering on the foreground region. Note that a model of this type would also account in a straightforward manner for the observation that the discrimination of decrements is generally more difficult than the discrimination of increments, simply because the signals are expected to be smaller: in the decrement discrimination, each high-contrast border patch has at most two low-contrast patches in its immediate neighborhood, while the foreground high-contrast patches always have five low-contrast patches in their immediate neighborhood.

5.3. Dipper functions

Most classical texture-segmentation studies test observers' ability to detect a discontinuity, which means that the border- or segmentation-signal is at threshold. Suprathreshold discontinuities have not received much attention, however. Previously, Nothdurft has studied suprathreshold discontinuities in a task where observers had to match salience across different feature dimensions (Nothdurft, 1993, 1994). Here, we employed a discontinuity discrimination task, allowing us to characterize processing of suprathreshold discontinuities within a feature map.

Similar to classical contrast discrimination studies (Legge & Foley, 1980; Wilson, 1980; Bradley & Ohzawa, 1986), we observe a dipper-type behavior: in a discrimination task where x and $x+\Delta x$ have to be discriminated, increasing pedestal signal, x, first leads to an improvement in discriminability, followed by a performance deterioration for a further increase in pedestal signal. The difference to the classical studies is that the relevant discrimination signal is now a spatial contrast difference (second-stage signal). Note that in the normal contrast discrimination tasks, it is impossible to discern first- and second-stage effects, since the first- and second-stage signals are not independently varied. Our data suggest that to observe a dipper in a discrimination task, the background is critical.

One popular way to account for the dipper function is to assume response nonlinearities or, specifically, to assume a sigmoidal contrast-response function (Nachmias & Sansbury, 1974; Wilson, 1980): discrimination sensitivity (as reflected by the slope of the contrast-response function) is maximal for spatial contrast differences in an intermediate range but drops for both stronger and weaker contrast difference signals. Another popular way to account for the response nonlinearities is to assume nonlinearities in the noise: the initial decline in the dipper function can be explained by uncertainty effects (Pelli, 1985), while the subsequent rise (reflecting a Weber Law-type behavior) can be explained by a noise that increases with the response level (Green & Swets, 1966). Dipper functions can also be affected by local light adaptation, sometimes leading to a second dip (Kingdom & Whittle, 1996); these effects, however, occur only at lower spatial frequencies and are not expected to have affected our results. Finally, the shape of the dipper function will depend also on the nature of interactions between the target and distractor, that are indicated by the failure of the IPM. Without a specific model in mind, however, it is difficult to make more precise predictions of how a global-competition model, or a global-response normalization model, would affect the dipper functions observed here.

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